A NEW APPROACH FOR ESTIMATING TOURISM -INDUCED ELECTRICITY CONSUMPTION

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Abstract:

Tourism has received an increasing attention due to its importance and benefits to economy during the last decades. However, tourism is considered to be highly climate-sensitive economic sector and in the same time a non-negligible contributor to climate change through GHG emissions derived specially from the different economic sectors (mainly transport and accommodation) involved in the tourist activities. In this paper, the tourism contribution with all its components parts is considered to investigate the electricity consumption in a case study of Balearics Islands (Spain). On the basis of a daily traditional model, and using the daily stocks of the population, it is shown how tourist load influence the electricity consumption in a high tourism intensive region.

Keywords: Electricity demand, tourism contribution, sustainable tourism, daily data.

JEL codes: L83, O13, Q41

1. INTRODUCTION

International tourism is considered nowadays one of the most important industries in the world, with an annual volume of 900 million arrivals (UNWTO, 2008) and a projection that this number will continue growing to 1.6 billion worldwide by 2020. In terms of economic importance, the Tourism Satellite Accounts elaborated by the World Travel & Tourism Council estimates the contribution of travel and tourism to World Gross Domestic Product at 9.9% in 2008, a percentage that is expected to continue growing to 10.5% by 2018 (WTTC, 2008).

Despite the economic significance of tourism in the economy, the sector is a major source of environmental impacts and resource consumption. It has been recognized that to be able to assess and improve sustainable development, accounting for a sector's performance should not only address the economic contribution but also environmental and social dimensions (Gray and Bebbington, 1993). In response to this recognition, additional methods for auditing performance have evolved, including lifecycle assessment (Hernández and León, 2007; Becken and Simmons, 2008) and ecological footprinting (Gössling et al., 2002; Patterson et al. 2007).

Although the contribution of tourism has been recognized as potentially considerable (Gössling, 2002), only very recently, literature have started to study energy consumption by tourist activities and the resulting greenhouse gas emissions that contribute to the anthropogenic component of global warming (Cárdenas and Rosselló, 2008). Thus, it is being fueled by a great recognition that tourism industry is also one of the largest consumers of energy, particularly it is needed to facilitate transportation of travelers, as well as to provide amenities and supporting facilities at the destinations visited (Becken, 2002; Becken & Simmons, 2002, Becken et al., 2001, 2003; Gossling, 2000; Gossling et al., 2002; Tabatchnaia-Tamirisa et al., 1997).

The use of energy and the contribution to greenhouse gas (GHG) emissions has benefit from a special attention in the case to the use of air transport. Price & Probert (1995) discussed environment impacts for air travel for a more general perspective but without particular reference to tourism. Penner et al. (1999) pointed out the difficulty to quantify the contribution of the greenhouse gases to global warming. However, some recent works examined the environmental impact of air travel. In particular, energy use and GHG emissions have been discussed by Gössling (2000), Gossling *et al.* (2005) and Peeters and Schouten (2006) by giving a figure of 60–95% of the contribution of an average trip involving air transport to global warming. A comprehensive discussion of the externalities of aviation, such as air pollution, noise, accidents, and congestion, is provided by Janic (1999). Becken (2002a) revealed that the energy use of up to 27.8 PJ is resulting from international air travel to New Zealand.

Additionally, accommodation sector and other complementary tourism industries have also been analyzed in the context of tourism energy use. Some pioneer studies have focused on a relationship between energy intensity and building characteristics highlighting the variety of the energy used by the different establishments, as well as the environment impact of their production (Becken et al., 2001; Deng and Burnett, 2000; Simmons and Lewis, 2001). Thus, Becken et al (2001) found that hotels are energy intensive and the average consumption per bed night range at 130MJ in the case of New Zealand. However the scientific data limitation in this area of research, makes it difficult to allocate a certain amounts of energy use for different accommodation establishments, and therefore a degree of uncertainty should considered.

From the literature review all these studies have considered sub-sectors of the tourist industry in order to accomplish to the calculation of the contribution of tourism to energy consumption. The reason for this desegregation can be found in the fact that tourism is not recognized as an economic sector in the traditional economic classification and their full consideration constitutes a problem because of the mixture nature of some of the sub-sectors that can be included in the tourists' product.[1] Nevertheless, it is important to ascribe an environmental responsibility to tourism activities in the sense that they can be regionally relevant for promoting or discouraging tourism development policies. Thus, to derive national and global estimates of that contribution it is necessary to develop methodologies for efficiently assessing tourism's contribution to greenhouse gas emissions, as well as key areas within tourism that should be targeted for mitigation strategies.

Consequently, the main objective of this paper is to make a contribution to the evaluation of tourism impact to energy consumption by estimating an electricity demand model that introduces the stock of tourists that contributes to this demand. Thus, using the isolated and highly tourist destination of the Balearic Islands (Spain), the daily electricity demand is modeled mainly as an explanation of the meteorological conditions of the archipelago, a set of labor calendar variables that controls the working and non-working days and the stock of tourism that are present in the islands during a day.

The paper is structured as follows. Section 2 reviews the literature on electricity demand modeling providing the methodological underpinnings for the study. Section 3 provides major details about data with special emphasis on the calculation of the daily stock of tourists. Section 4 presents the results and the discussions. Finally, Section 5 concludes.

2. METHODOLOGY

Because of the fact that electricity cannot be stored, producers have to anticipate future demand in a very accurate way, specially that energy sector is very sensitive to exogenous

[1] For instance, restaurants and some specific commercial activities can have both a local and a tourist component that is often difficult to isolate.

factors such as weather conditions and other socio-economical factors. For short term load modelling and forecasting electricity consumption several variables should be considered, such as time factors, weather data, and other factors such as electricity prices, social events and possible customers' classes. Meanwhile different approaches have been adopted to combine these variables, given birth to a variety of models.

2.1. Exogenous variables

Economic time series often contain multiple periodic cycles of different lengths. In particular electricity demand time series often exhibits a persistent trend and different seasonality patterns. In the context of high frequency data (hourly or daily) the predominance of the working time effect is patent and often highlighted by applied exercises (Pardo et al., 2002; Valor et al., 2001).

One of the most common ways to capture the deterministic pattern exhibited in the electricity load data is the use of dummy variables referred to the hour of the day, day of the week or month of the year. In the same way anomalous events related to holidays, special days are often captured by dummy variables. In any case, the presence of different load profiles between the week days and weekends was under study by Ramanathan et al (1997), where models were built for two categories, separating normal days and weekends in the electricity hourly load modelling. However this approach revealed inappropriate for the case of public holidays, long weekends and vacation periods and different techniques were applied such as smoothing over or replacement (Taylor et al., 2006; Smith, 2000; Hippert et al., 2005).

Recent works have illustrated the effectiveness of modelling holidays using dummy variables. Moreover a type of classification was implemented to identify similarities among patterns reducing the number of dummies to six in a study of Cottet et al., (2003); three in a work of Pardo et al. (2002) and one in Soares and Souza (2006) study. Cancelo et al.(2008), in the case of Spain, specified a set of models for every single day of the week and examined their performance in the short –term modelling electricity load.

Apart of the time factors, weather conditions are considered one of the most influential exogenous variables, especially for short term load forecasting (Valor et al., 2001). Various variables could be considered, but temperature and humidity are the most commonly used load predictors (Mirasgedis et al., 2006). Among the weather variables considered two composite weather indicators, the THI (Temperature Heating Index) and WCI (Wind Chill index) are broadly used (Rahman et al. 1993). Yan (1998) studied electricity en residential sector in Hong Kong using a weather stress index, and examined how it affect the use of electricity en air-cooling. Ranjain and Jain (1999) categorized electricity en Delhi into four seasons and derived empirical models based on population and weather conditions.

The relationship between load and temperature is complex for a number of reasons. On the one hand, the literature suggested that it is non-linear and U-shaped as long as there is enough variation in the sample (Engel, Granger, Rice, 1992). Thus, there is an interval where the electricity load is slightly unchanged to the temperature variations, once out of this interval electricity demand jumps with both increasing and decreasing temperatures. That is, depending on the coldness, or heat of weather, people will increase or decrease the use of electric heating appliances or air conditioners. On the other hand the response is asymmetric, in the sense that the impact of one degree increase for high temperature is not necessary equal to the effect of one degree decrease for low temperature (Valor et al. 2001).Smith (2000) found that temperature has different effect on the load for working and non working days, similarly the effect is different in workplaces compared to a private residences. Not only the relationship temperature load change during the time of the year, but depend as well to what can be described as a temperature hysteresis (Hyde & Hodnett (1997).

In models using low frequency data (monthly, quarterly or annually) factors related to electricity prices can also be included in load forecasting models. For non-residential and cost-sensitive industrial or institutional consumers the financial incentives to adjust loads can be significant. Chen et al. (2001) reported that the inclusion of spot price data allowed obtaining more accurate estimates of the Ontario Hydro load. However in a number of models that included a price as an explanatory variable to explain energy load, it was proved that the price factor revealed to be insignificant in short run (Zachariadis et al, 2007). Although it would be useful to incorporate price effect in the forecast, the historical data does not provide sufficient information to do so. It should be recognized though that for most industries in this sector, electricity costs are only a small proportion of total operating costs and the ability to switch fuel types is limited at best. Electricity prices on the whole are therefore not expected to have a significant effect on short-term demand in this sector, although they may result in some longer term impacts associated with efficiency savings and fuel switching where it is feasible.

2.2. The model

Modeling electricity consumption has received considerable attention over the past fifty years, and a large variety of methods have been tried for loading or forecasting, with varying degree of success. Weron (2006) classified these methods into two broad categories: First, artificial intelligence-based (or non-parametric) techniques, like neural networks, fuzzy logic, expert systems and support vector machine, and the second category is Statistical approaches, including similar-day (or naïve), exponential smoothing, regression and time series methods. Both artificial intelligence based and the statistical methods display the current load value by using a mathematical combination of the previous loads and/or current values of exogenous factors, typically weather and social variables.

Regarding Artificial intelligence-based methods, artificial neutral network (ANN) have probably received the most attention because of their straightforward implementation and relatively good performance. Other non-parametric techniques, like fuzzy logic, expert systems and support vector machines have been also applied, however, typically in conjunction with ANN or statistical models. Many studies examined the performance of ANN models comparing them with conventional approaches (Khotanzad et al. 1998; Hippert et al., 2005; Taylor et al., 2006; Darbellay and Salma, 2000), however there is no empirical evidence about the superiority of a model upon others. Probably the popularity of the ANN approach stems from the fact that no prior modelling experience is required to obtain reasonable load forecasts Nevertheless, the limitation of these methods lies in the fact that it is difficult to estimate a quantification of the relationship between the variables involved in the forecasting exercise (Smith, M., 1995).

Statistical approaches usually require represent electricity load as a function of different factors. A basic and traditional structure decomposes the observed load into four components: the normal load, the weather sensitive part, special events and a random component. Assuming the traditional aggregated energy demand relationship (Cancelo et al., 2008, Considine, T, J., 2000) a log-linear model can be expressed analytically as follow:

$$\ln C_t = p_t + s_t + CSD_t + CWEA_t + U_t \qquad [1]$$

Where C_t denote the electricity consumption on day t, p_t denoting the trend and s_t (part of) the deterministic pattern; CSD_t is the contribution of special days; $CWEA_t$ is the contribution of meteorological variables; and u_t is a stationary disturbance that may display some short-term, transitory dynamics. It should be highlighted how a correct diagnostic of the

U_t term will improve the performance of the prediction in one hand, and will increase the efficiency of the estimations in another hand.

Many approaches have been applied to model the stochastic nature of demand. The autoregressive methods were usually used as benchmarks for other methods, whereas autoregressive moving average models have been considerably used to load modelling and forecasting. Standard ARMA analysis rests on the simplifying assumption that the mean and unconditional variances of time series are independent of time, i.e., the series are stationary. The plot of autocorrelation function and partial autocorrelation function as well some conventional tests like Augmented Dickey Fuller test are used to decide whether a data series are stationary or not.

The relative success of ARMA processes in modeling and forecasting short-term electricity load, rely on their capability to generalize the time dependence and perform better than autocorrelation adjustment models used by, in addition to their flexibility to capture a variety of dynamic effects (Ramanathan et al., 1997; Pardo et al., 2002; Taylor, 2003). Usually, ARMA models are used for prediction purposes. Then, Chen et al. (1995) used an adaptive ARMA model for one week ahead load forecasts. Huang and Shih (2003) proposed and iterative scheme for calibrating ARMA process ensuring the performance of short-term load forecast. Soares and Medeiros (2005) used a SARIMA model as a benchmark and compared it to a general ARMA models on hourly loads from Rio de Janeiro, Brazil. In addition, more general models were used by including exogenous variables, and performed well in modelling and forecasting. Juberias et al. (1999) developed a real time load forecasting ARIMA model for the Spanish market that included a meteorological factor as an explanatory variable. In the same line Cancelo et al. (2008) found that a seasonal ARIMA model outperformed the benchmark methods used by other competing organizations and stood superior to forecast daily and weekly electricity load for the Spanish system operator.

Furthermore, it is relevant to mention that the good performance of ARMA models in forecasting is intrinsically associated with a good specification of the best ARMA model that can handle different exogenous effects as well as seasonality in electricity load (Pardo et al 2002).

Conventionally, in ARMA models, the variance of the disturbance is assumed to be constant. However, during the last years it has shown how many financial and economic time series exhibit periods of unusual large volatility, followed by periods of tranquillity. This circumstance suggests a form of heteroscedasticity in which the variance of the disturbance depends on the size of preceding disturbance and hence the conditional variance is not constant over the sample period.

Engle (1982) showed that is possible to model the mean and the variance of a series simultaneously by a model named ARCH; whereas the Box-Jenkins (1976) modelled only the mean series. Bollerslev (1986) extended Engels´ original work by developing a technique that allows the conditional variance to be ARMA process and that extended process is known as the GARCH process. The conditional variance equation of GARCH (p,q) model can be shown as:

$$h_t=\alpha_0+\alpha_1\varepsilon_{t-1}^2+\ldots\ldots\ldots\ldots+\alpha_q\varepsilon_{t-q}^2+\theta_1 h_{t-1}+\ldots\ldots\ldots+\theta_p h_{t-p} \qquad [2]$$

Where, p and q are the order and are non-negative integers. Or using the lag operator, a GARCH (p,q) model is in the form

$$h_t=\alpha_0+\alpha(B)\,\varepsilon_t^2+\theta\,(B)\,h_t \qquad [3]$$

Where, $p \geq 0$, $q>0, \alpha_0>0$, $\alpha_i \geq 0$, $i=1,2,\ldots.q$, $\theta_j \geq 0, j=1,2,\ldots.p$, and to keep the second order stationarity constraint GARCH models also demand $\alpha(B)+\theta(B)<1$

In practice since there is dependence in the residual series of the electricity load models, ARCH class model can attempt to capture such dependence. Considering that the order of ARCH effect is relatively high, ARMA-GARCH models are preferred to pre-filter the series and capture the most important dependencies in the residual series. Then, some works have started to show how GARCH models can improve previous models. Thus, Chen et al., (2006) used a GARCH class models to model and forecast electricity load and found that they perform better than classical ARMA models. In the same line Hor et al., (2006) used GARCH to model the residuals in the student-t distribution and to estimate the maximum load demand that would be likely to occur in a short-term.

The models considered in this paper is a modified version of the Seasonal Autoregressive Moving Average (SARMA) model, with dummy variables to correct the effects of holidays and special days, weather variations and stock population, in addition to a generalized autoregressive conditional heteroskedasticity (GARCH) model.

3. DATA ANALYSIS

The proposed electricity models developed in this paper takes the case study of daily data consumption of the isolated electricity system of the Balearic Islands (Spain). The power system in Balearic Islands is responsible for supplying electricity to 1 million of residents and 13 of tourists annually according to the official statistics. In reference to the tourist population it is important to highlight that the average length of stay of a tourist is about 9 days, and the fact that the climate conditions of the archipelago explain the high level of seasonality that characterize tourism in the islands that accounts for 60% of total arrivals from June to September.

3.1. Electricity data

Data of electricity consumption for the Balearic Islands (BAL) was provided by Red Electrica Española, the Spanish System Operator, and ranges from January 1995 to September 2007. The data set used comprises daily electricity demand (E) in MW h for the entire period under consideration. The daily demand data aggregate all sectors of economic activity (industrial, commercial, residential, and agriculture), as sector disaggregated data were not available for this time frequency.

[*Insert Figure 1 about here*]

In Figure 1, it is clearly observed that a strong trend do exist in the daily electricity demand. This trend has been often observed in various studies, more precisely Cancelo and Espasa (1996), for the Spanish case, the data showed a positive trend for the period 1983-1988 that was attributed to social, economic, and demographic factors. Previous works have discussed also significant seasonal daily and monthly components in the electricity load series (Valor et al., 2001). In order to capture them, different dummy variables were introduced. Anomalous events related to holidays, or special days, have also been considered in order to capture the different electricity patterns shown traditionally by population in this special days. Thus, it is expected that the electricity consumption decreases considerably during holidays as well as in weekend.

3.2. Weather data

Historical weather data required by the proposed models for the period were supplied by the *Centre de Recerca Econòmica* and comes from the Balearics meteorological center. The experience of many utilities indicates that the weather elements, which influence electricity demand, consist of temperature, humidity, wind and precipitation in a decreasing order of importance (Engle et al. 1992). However, the influence of a considerable number of meteorological parameters on electricity demand of Spain was analyzed by Cancelo y Espasa (1996) affirming that primary temperature and secondary humidity are the most significant of them.

As literature has traditionally considered and as clearly depicted in Figure 1 the non-linear influence of temperature on electricity demand suggests the use of two temperature derived functions, the heating degree-days (HDD) and the cooling degree-days (CDD), thus separating the winter and summer data. In dealing with the non-linearity of the temperature effect, the most frequent posture in the literature is to segment temperature in terms of the HDD and CDD that can be defined as:

$$HDD_t = \text{Max}\,(T_{ref} - T_t, 0) \qquad [4]$$

$$CDD_t = \text{Max}\,(T_t - T_{ref}, 0) \qquad [5]$$

T_t is the weighted average temperature for the day t and T_{ref} is a reference temperature that should be adequately selected to separate the heat and cold branches of the demand-temperature relationship. These functions reflect in combination the number of days on which the temperature stands below or above the thresholds of cold and heat, and by how many degrees. Since there is no strict quantification of the values of the "threshold" temperatures, there can be many different versions of the functions HDD and CDD. In the context of this study the reference temperature has been selected to be equal to 17 °C for high temperatures and 12 °C for low temperatures, which is the interval of temperature at which, as shown in Figure 2, the influence of temperature is minimized and electricity demand is inelastic to temperature changes.

[*Insert Figure 2 about here*]

Additionally, because of the special high degree of humidity that characterize the Balearic Islands that, the Heat index (HI) was introduced as an alternative of the use of the simple mean temperature variable. Measurements have been taken based on subjective descriptions of how hot subjects feel for a given temperature and humidity, allowing an index to be made which corresponds a temperature and humidity combination to a higher temperature in dry air. Whatever the case, the most used formulation of the HI was proposed by Steadman (1979) and is also adopted in this study.[2] Otherwise, for the measurement of the Balearic index the population weighted temperature index has been constructed from the mean daily temperatures measured at the different islands separately. The reason why the population has been selected as a weighting factor is that climate influences the electric consumption through the response to people to weather; the people will increase or decrease the use of electricity appliances or air conditioners. Thus the higher the population, the higher the influence of weather conditions in electricity demand.

[2] Then, $HI = -42.379 + 2.04901523T + 10.14333127R - 0.22475541TR - 6.83783 \cdot 10^{-3}T^2 - 5.48171710^{-2}R^2 + 1.22874 \cdot 10^{-3}T^{2}R + 8.5282 \cdot 10^{-4}TR^2 - 1.99 \cdot 10^{-6}T^2R^2$, with T = ambient dry bulb temperature degrees in Fahrenheit and R = relative humidity.

Thus, Figure 3 presents daily electricity consumption in Balearics versus HDD and CDD build on the basis of the HI (HTEMPHI and LTEMPHI, respectively). It is clear that the two seasonal branches are separated into two functions, the first one for high temperatures and the second for low temperatures.

[*Insert Figure 3 about here*]

3.3. The daily population stock

The annually demographic load that can be present in an area or region could be largely different from the data collected by the census office. Mainly, this divergence is due to the high frequent movement of the people to destinations outside the places where they normally live and it includes movements for all purposes, family, studies, work or leisure. The Balearic Islands, with its high specialization in tourism industry, are considered one of the regions with this special pattern. In fact, tourist movements in the Balearics Islands are very important and can double the amount of resident in some days of the year.

In this context, Mateu and Riera (2007) developed the IDPH[3] measure, that captures the stock of people, at a daily level, that were on each one of the Balearic Islands based on the resident population data and the arrivals and departures from the airports and ports. The IDPH has proven an accurate approximation to measure the demographic pressure in Balearic Islands and is derived from the following expression:

[3] From the Catalan abbreviation of Indicador Diari de Pressió Humana (=Human Pressure Daily Indicator).

$$IDPHD = PR0 + \sum_{d=1}^{D}(Ed - Sd) + \sum_{d=1}^{D}(Vd) \qquad [6]$$

Where PR0 is the resident population on the first day of each year based on the official statistics; *Ed-Sd* is the difference between the entry and exit quantities of individuals, derived from airports and ports registrations; and *Vd* stands for the natural growth of the population as consequence of births and deaths

For the special purposes of this work the IDPH is separated into the daily stock of the resident population (IDPH_RES) and the daily stock of the tourist population (IDPH_NORES) in order to isolate the effect of the tourist sector on electricity consumption. This separation was based on the *Familitur* data from where it is possible to estimate how many residents are on tourism monthly. In any case, data from Familitur is only available at the Balearic Islands level being not possible to separate the two groups for each one of the islands. For the case of the Balearic Islands the separation of the IDPH into residents and non-residents can be shown in Figure 4.

[*Insert Figure 4 about here*]

4. RESULTS AND DISCUSSIONS

Following considerations mentioned above the equation below was set to estimate the daily electricity demand for the case of the Balearic Islands:

$$Ln(E_t)=c+\alpha t+k_1*HTempHI_t+k_2*HTempHI_t^2+l_1*LTempHI_t+l_2*LTempHI_t^2+\sum_{i=2}^{7}(di*Dit)+\sum_{j=2}^{12}(fj*Mjt)+\sum_{k=1}^{16}e_k*SD_{kt}+p_1*IDPH_{RES}+p_2*IDPH_{NORES}+e_t \quad [7]$$

It should be noted how the electricity demand variable (E) is taken in natural logarithm; D_{it} and M_{jt} are dummy variables that control for the day of the week (i) and the moth of the year (j); SD_k are dummy variables that controls the non-labor and special holidays days; c, α, k_1, k_2, l_1, l_2, d_i (i from 2 to 7), f_j (j from 2 to 12), e_k (k from1 to 16) $p_1$and p_2 are the coefficients to be estimated from the regression analysis and e_t is the residual term distributed normally and independently.

The results of the models are reported in Table1. The adjusted R^2, the Akaike Info Criterion (AIC) and the Schwarz Criterion (SC) were used to select the best model that fit our data, and were GARCH model revealed a high consistency with comparison with ARMA model, in addition to F-test for overall significance of the model and a t-test for testing the strength of each of its individual coefficients. The main results obtained with the introduction of the dynamic structure are presented in Table 1, where it can be shown how different autoregressive terms (AR for simple autoregressive terms, and SAR for seasonal autoregressive terms

The adjusted R-squared of the estimated models can be qualified as good being higher than 0.96 for both models. In addition a subset of the variables in the model is tested for statistical significance to examine if they can be omitted. Each of the insignificant variables is deleted sequentially from the general dynamic model, while the significant parameters at 1%; 5% and 10% levels are retained.

[*Insert Table 1 about here*]

For weather parameters, ARMA model shows that high temperature heating index and low temperature heating index are both significant at 1% level. The squared term of these variables were added to the model of the Balearic Islands in order to capture non–linear relationships and reveal in ARMA model 5% significance for high temperatures and 1% significance level for low temperatures, whereas in GARCH model the parameters mentioned before are significant at 1% level except the low temperature heating index that is significant at 5% leve . Because of the non-linear relationship between electricity consumption and temperature, the obtained relationship between these two variables is investigated using the concept of elasticity, a standard measure to evaluate the sensibility of electricity load to temperature changes (Valor et al, 2001), that for this case study can be defined as:

$$\epsilon_{HTHI} = \frac{HTHI}{E_{HTHI}} * f'(\text{HTEMHI}) \qquad [8]$$

$$\epsilon_{LTHI} = \frac{LTHI}{E_{LTHI}} * g'(\text{LTEMHI}) \qquad [9]$$

Where ϵ_{HTHI} and ϵ_{LTHI} are the elasticities for the high and low temperatures using the heat index; f'(HTHI) and g'(LTHI) are the first derivatives of the electricity demand function with respect to HTEMHI and LTEMHI, respectively.

In Figure 6 the elasticity estimations are plotted versus high and low temperature using both approaches ARMA and GARCH models, we observe that elasticity for low temperatures is higher than its correspondent at high temperatures, in other words the residents and non-residents have higher sensitivity toward temperature in winter than in summer. Moreover the GARCH models are less steep with elasticity almost equal, while in

ARMA model this sensibility is almost equal till high and low temperatures reach 7CDD and 7 HDD respectively, then the gap is visible between the two temperature's ranges for values superiors to 8 CDD and 8 HDD respectively.

Figure 7 depicts the elasticity estimations for high and low temperature heating index, for Balearics Islands from 1994 to 2006. The data show an increasing trend for both high and low temperatures in the case of ARMA model, with a slight positive difference in the case of low temperatures, means that along the time period 1994; 2006 electricity users were slightly more sensitive to cold than to heat. In the other hand, the positive trends disappeared when we applied GARCH model, as we had a steady average elasticity for low temperatures and a smoothly decreasing trend for high temperatures. For both models, maximum elasticities are observed in years 2003 and 2005 for high and low temperatures heating index respectively, where in 2003 the annual average elasticity reached 3.7% coinciding with a historical high temperature recorded during this period. Identically the higher value of annual average elasticity for low temperatures was logged in year 2005 which was characterized with a colder winter.

[*Insert Figure 5 about here*]

[*Insert Figure 6 about here*]

For the population stock variable, both models ARMA and GARCH in Table1 show a high significance level for both residents and non-residents, and a positive sign that is interpreted by the fact that an increase in the population (residents or non-residents) will be associated with an increase in electricity consumption. To understand the effect of this exogenous factor on the electricity load different scenarios has been simulated in order to capture the sensitivity of the population toward energy use. Table 2 gathers the results of the different simulations of the effect induced by various raise in the two population stocks (residents and non-residents), the percentage rates 5%; 8% and 10% were selected to simulate these scenarios. As there is an increasing gap between the two populations during the period set of our study, simulations were done for two different years, 1999 and 2006.

[*Insert Table 2 about here*]

Results show how an increase in population stock for respectively residents and non residents is associated with an increase of electricity consumption, with relatively high annual rates for residents in the three scenarios and in both years 1999 and 2006. Regarding the comparison of the results got from ARMA and GARCH approaches, a small difference is observed between the growth rates of the non residents' population, whereas residents' population is characterized by a higher growth rates in the three scenarios. To highlight this difference, the example of a 10% increase scenario, shows that the means of the growth rate recorded in years 1999 and 2006 respectively, passed from 3.5% and 4.3% in ARIMA approach to 4.8% and 5.8% in GARCH model

High electricity consumptions are observed in summer, either for residents or nonresidents models, whereas low rates are depicted in autumn and winter. Furthermore, a sensitivity analysis of electricity consumption is done for the months February, March, April, August and November. Minimum rates of electricity growth for both residents and nonresidents are obtained in April and November, as in a simulation of a 10% increase in absolute value of nonresident's population of Balearics; the average electricity growth rate for non residents is 2.86% in August compared to 0.38% registered in January and February, this result is shared between ARMA and GARCH approaches, whereas for resident the monthly variability is not higher and the rates fluctuate around an average of 3.5% in the case of ARMA model and 4.7% for GARCH model. These results trigger other questions such as, what would happen if the resident or nonresidents' population increased by a fixed amount? Has it the same effect on electricity consumption if we simulate an increase in population in February instead of August?

Different simulations were processed as intent to answer the questions set above. Thus, in Table 3, simulations were run of an increase of the Balearics' resident and nonresident population separately, by using both ARMA and GARCH approaches and adding a 3%, 5% and 10% of the resident and nonresident average population respectively. The results show a higher sensitivity of electricity demand in case of resident than nonresident; in fact for ARMA model the means of electricity demand growth rates reached 53.7%, 50.7% and 49.5% for 10%, 5% and 3% increases respectively of resident population mean, compared to 13.1%, 12.5% and 12.2% for the case of nonresident population. Using GARCH model only the growth rates of the resident population are affected, they "jumped" to 78.5%, 73.9% and 72.1% for 10%, 5% and 3% increases respectively.

[*Insert Table 3 about here*]

Another simulation that is worth to be mentioned is a scenario with the absence of tourists; simultaneously an evaluation of resident's weight on electricity consumption is evaluated. Results revealed for both models a decrease of an average of 12% of the total electricity consumed in the case of non residents, and an average of 33% in the case of residents, in other words the third of the total electricity demanded in Balearics islands.

These results are for a considerable importance for tourism planners, to mitigate the effect of high energy consumption on the environment. Such a result can be used as a basis for measures to regulate, or otherwise maintain a control on visitor flows in congested places, or to guide planning decisions about the number of population stock that may be acceptable in an area in peak season.

5. CONCLUSIONS

As awareness of tourism's energy impacts on global environmental increases, and as knowledge of energy impacts and its associated costs on tourism destination sustainability grows, so does the need for the planners to develop proactive energy management strategies. However, the literature reveals how the no recognition of the tourists sector by the traditional public economic accounts has derived in sectorial studies when tourism associated costs have been evaluated.

Assessing future energy demand responses requires consideration of the dynamics of historic energy sensitivities. A methodological innovation of this model is the inclusion of tourist population stock to capture the dynamic characteristics of energy responses. If energy response sensitivity has a time varying component using an average response could significantly over or under account for changes on energy load and its concomitant GHG emissions in tourism destinations.

In this article we examined the feasibility of applying two models (ARMA and GARCH) to daily electricity demand in Balearics Islands, showing a high level of significance of both resident and non resident population stocks. Strong evidence has been found revealing that daily electricity load can be characterized by the GARCH models. The sum of the GARCH coefficients is close to one, which means a persistence of the conditional variance, also it has been demonstrated that GARCH model perform better than ARMA model in the deviation measurement criteria.

The findings suggest an increasing sensitivity of electricity demand in response to "stock population", this increasing sensitivity is likely a result of increasing number of tourists during the peak season. However, the analysis has revealed that the sensitivity of electricity load to population stock variable has increased along time for residents and non-residents, with higher sensitivity for resident case. Furthermore, a simulation study has been undertaken through a hypothesized increase of 3%, 5% and 10% of the resident and non-resident average population respectively. The main results of the simulation show high growth rates of electricity demand for both residents and non-residents in the summer, in addition to a relative insensitivity of electric demand between resident and non-resident during summertime. Furthermore, a simulation of an increase of non-resident population in February or November is associated with a relatively low growth rate of electricity consumption.

This work is a step forward reducing the scarcity of investigation in the area of tourism impact on energy consumption, and so providing information for the tourism industry as well as policy makers. Future research will have to deal with de possibility to evaluate the tourism responsibility in determining electricity load in each one of the Balearic Islands by considering the variability within the year of the total population stock, assuming that the main fluctuation of the variable is caused by the tourist population. These results should be compared with those obtained in this work in order to validate them.

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Table 1. Estimated models for electricity consumption in the Balearics

	Balearics	
	SARIMA	GARCH
@TREND	0.000121***	0.000116***
SD05_1	-0.084873***	-0.103428***
SD06_1	-0.016502	0.000852
SD16_1	-0.034970***	-0.040611***
SD20_1	-0.017176*	0.006522
SD28_2	-0.080794***	-0.089668***
SD01_3	0.012277	0.017754*
SD30_4	-0.074209***	-0.097090***
SD14_8	-0.090787***	-0.094607***
SD11_10	-0.093382***	-0.103354***
SD12_10	-0.034739***	-0.018066
SD31_10	-0.161923***	-0.164223***
SD01_11	-0.030237***	-0.007263
SD05_12	-0.108315***	-0.105519***
SD06_12	-0.045012***	-0.022928**
SD07_12	-0.089030***	-0.095638***
SD09_12	0.028125**	0.011331
SD24_12	-0.112713***	-0.125040***
SD25_12	-0.093491***	-0.101865***
SD31_12	-0.078890***	-0.095588***
SDJVS_ST	-0.069747***	-0.049308***
HTEMPHIP	0.010488***	0.005321***
HTEMPHIP^2	0.000278**	0.000351***
LTEMPHIP	0.007386***	0.005248***
LTEMPHIP^2	0.000537***	0.000392**
C	8.480177***	8.325717***
IDPH_RES	4.34E-07***	3.93E-07***
IDPH_NORES	3.71E-07***	5.86E-07***
AR(1)	0.458179***	0.704687***
AR(2)	0.128453***	0.061863**
AR(3)	0.125815***	0.115401***
AR(4)	0.095278***	-
AR(7)	-0.256688***	
SAR(7)	0.694744***	0.284688***
MA(1)	-	-
Equation Statistics		
Adjusted R-Squared	0.971475	0.965592
Log likelihood	6154.008	6331.140
Durbin-Watson stat	1.893018	2.316683
AIC	-3.840886	-3.950403
SC	-3.751251	-3.855047
F-statistic	2354.644	1821.676
Proba(F-Statistic)	0.000000	0.000000

Note: *** significant at 1%, ** significant at 5%, * significant at 10%

Table 2: A simulation for electricity consumption growth of Balearics

			5% increase		8% increase		10% increase	
			resident	non resident	resident	non resident	resident	non resident
ARMA	Max	1999	1.8%	1.4%	2.9%	2.3%	3.6%	2.9%
	Mean	1999	1.7%	0.6%	2.8%	1.0%	3.5%	1.2%
	Max	2006	2.2%	1.5%	3.6%	2.4%	4.5%	3.0%
	Mean	2006	2.1%	0.5%	3.4%	0.8%	4.3%	1.0%
GARCH	Max	1999	2.4%	1.5%	3.9%	2.4%	4.9%	3.0%
	Mean	1999	2.4%	0.6%	3.8%	1.0%	4.8%	1.3%
	Max	2006	3.0%	1.6%	4.8%	2.5%	6.1%	3.1%
	Mean	2006	2.9%	0.5%	4.6%	0.8%	5.8%	1.0%

Table 3: Simulation from tourist and residents population growth

		3% increase		5% increase		10% increase	
		resident	non resident	resident	non resident	resident	non resident
ARMA	Mean	49.5%	12.2%	50.7%	12.5%	53.7%	13.1%
GARCH	Mean	72.10%	12.99%	73.92%	13.26%	78.56%	13.94%

Figure 1. Daily electricity consumption in the Balearic Islands

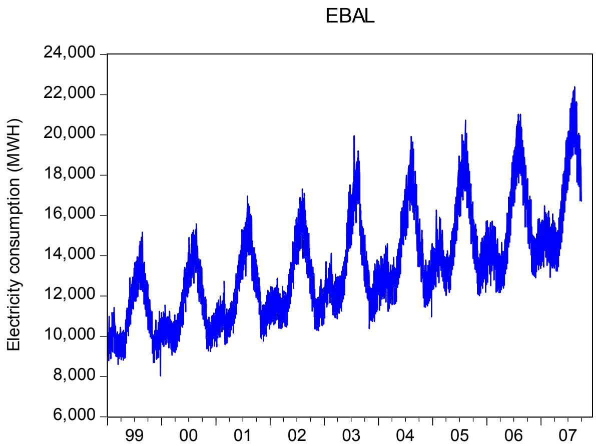

Fig.2 Daily Load and mean temperature in Balearics

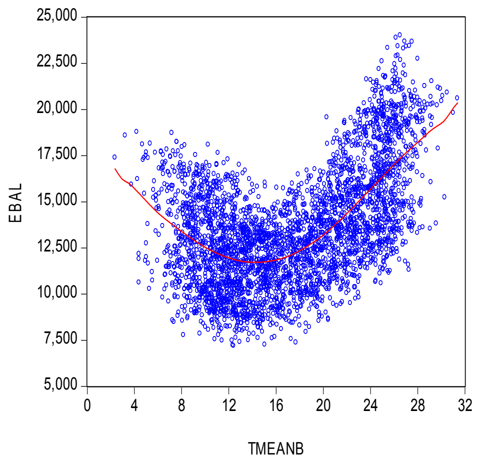

Fig.3. Daily electricity consumption & HDD and CDD in Balearics

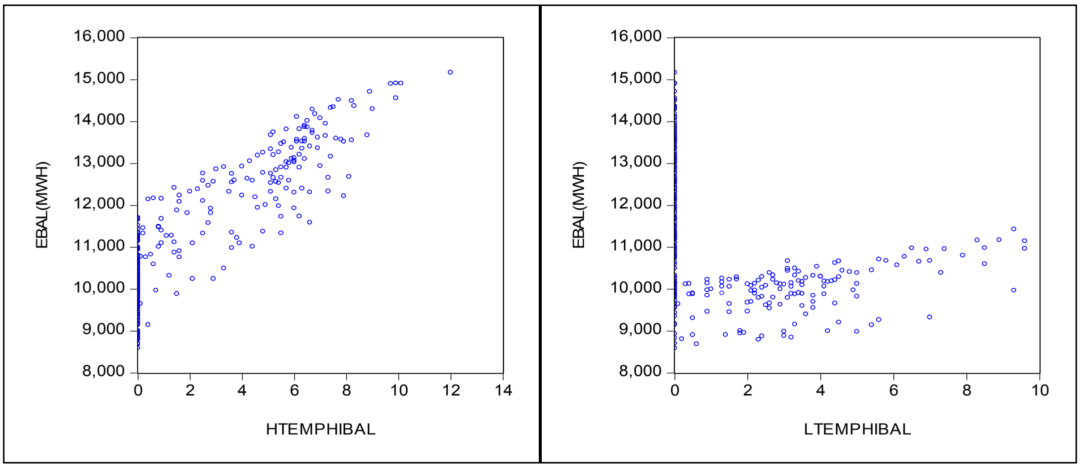

Figure 4. IDPH for the residents and for the tourists in the Balearics

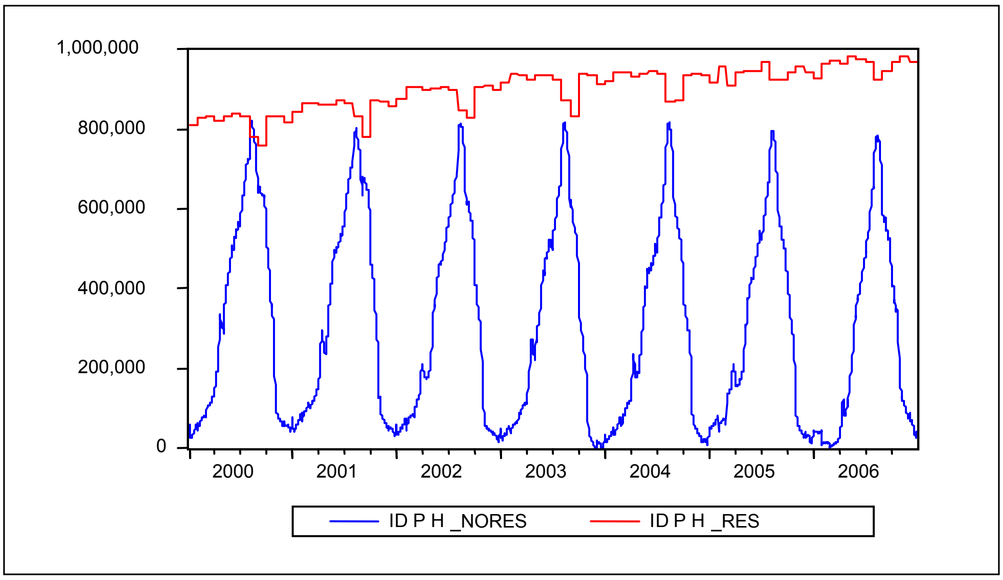

Figure 5. Daily elasticity estimations from the electricity demand function

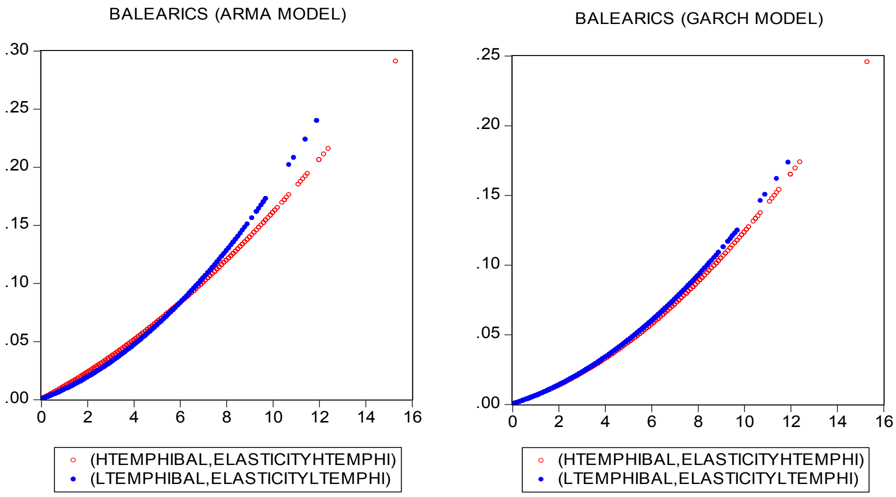

Figure 6. Yearly elasticity estimations from the electricity demand function